

WELCOME TO R - PROGRAMMING LANGUAGE

Regression Using R Language

- Language:

Introduction:

- * R is a programming and free software environment for statistical computing and graphics.*
- * An effective data handling and storage facility.*
- * A large, coherent, integrated collections of intermediate, tools for data analysis.*
- * Programming language includes conditions ops, user-defined, recursive functions and input & output facilities.*

Regression:

Intro:

- * It is introduced by “*Sir Francis Galton*”.
- * It means “*Stepping back towards the average*”.
- * Regression analysis the mathematical measure of the average relationship between two or more variables in terms of the original units of the data.
- * Estimation of regression is called regression analysis.

Regression in R Language:

Regression analysis is a widely used statistical tool to establish a relation model between two variables.

*One of these variable is called “**predictor variable**” whose value is gathered through experiments.*

*The other variable is called “**response variable**” whose value is derived from the predictor variable.*

Regression are two types:

- 1. Linear Regression*
- 2. Multiple Regression*

Linear Regression in R:

In linear regression these two variables are related through an equation, where exponent(power) of both these variables is 1.

*Mathematically a linear relationship represents a **straight line** when plotted as a graph.*

*A non-linear relationship where the exponent of any variable is not equal to 1 creates a **curve**.*

Formula for Linear Regression:

The general mathematical equation for a linear regression is-

$$Y = a + bX$$

$$Y = (\bar{Y} - b\bar{X}) + bX$$

$$Y = \bar{Y} + b(X - \bar{X})$$

$$Y = \bar{Y} + bx$$

Following is the description of the parameters used-

* Y is the response variable.

* X is the predictor variable.

* a and b are constants which are called the coefficients.

* b_{xy} is the parameter of regression

The Regression Model

The diagram illustrates the regression model equation $Y = \beta_0 + \beta_1 X + \epsilon$. The dependent variable Y is on the left. The equation is composed of three main terms: β_0 , $\beta_1 X$, and ϵ . Labels with arrows point to each term: "Y-intercept" points to β_0 , "Slope coefficient" points to β_1 , "Independent variable" points to X , and "Random error term" points to ϵ . A red bracket under $\beta_0 + \beta_1 X$ is labeled "Systematic component". Another red bracket under ϵ is labeled "Random component". The ϵ term is highlighted in yellow.

$$Y = \beta_0 + \beta_1 X + \epsilon$$

Labels and components:

- Dependent variable: Y
- Y-intercept: β_0
- Slope coefficient: β_1
- Independent variable: X
- Random error term: ϵ
- Systematic component: $\beta_0 + \beta_1 X$
- Random component: ϵ

Steps to Establish a Regression:

Carry out the experiment of gathering a sample of observed values of height and corresponding weight.

Create a relationship model using the *lm()* functions in R.

Get the coefficients from the model created and create the mathematical equation using these.

Get a summary of the relationship model to know the average error in prediction. Also called *residuals*.

To predict the weight of new persons, use the *predict()* function in R.

Input data:

Obtain the equation of two variables of regression for the following data and also find out the estimation of y of $x=180$.

x	176	154	148	166	172	124	190	135	155
y	88	61	59	70	88	65	92	52	65

lm() Function:

The function creates the relationship model between predictor and the response variable.

Syntax:

The basic syntax for `lm()` function in linear regression is

`lm(formula, data)`

Following is the description of the parameters used:

- * **formula** - symbol presentation the relation between predictor and response variable.
- * **data** - vector on which the formula will be applied.

Correlation Coefficient:

The correlation coefficient between two random variables X and Y is defined as

$$r_{xy} = \text{corr}(X, Y) = \frac{\text{cov}(X, Y)}{\sigma_x \sigma_y}$$

where,

$$\text{cov}(X, Y) = E[(X - \mu_x)(Y - \mu_y)]$$

It has a value -1 and $+1$, and it indicates the degree of linear dependence between the variables. It detects only linear dependence between two variables.

the estimate interpretation when both variables are nous:

Given a one unit increase in X , this is the expected change in Y , on average.

(This interpretation changes for categorical variables and variable transformation)

Standard Error:

The standard error is the estimated variability in a coefficient due to sampling variability i.e. a different sample means in different coefficients and the variability of coefficient across samples is estimated by the standard error of the respective coefficient.

ut:

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Go to file/function Addins

```
54,148,166,172,124,190,135,155,161)
,59,70,88,65,92,52,65,70)
```

```
lm()fuction
lm(y~x)
```

```
tion)
```

```
y ~ x)
```

```
0.5906
```

```
summary(relation))
```

```
y ~ x)
```

```
Q Median 3Q Max
-3.441 5.361 14.140
```

```
Estimate Std. Error t value Pr(>|t|)
-22.3772 21.5525 -1.038 0.32951
0.5906 0.1354 4.362 0.00241 **
```

```
es: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
Standard error: 7.926 on 8 degrees of freedom
R-squared: 0.704, Adjusted R-squared: 0.667
19.03 on 1 and 8 DF, p-value: 0.002406
```

Environment History Connections Tutorial

Import Dataset

Global Environment

Data

relation List of 12

Values

x	num [1:10]	176 154 148 166 172 124 190 135
y	num [1:10]	88 61 59 70 88 65 92 52 65 70

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Zoom Export

predict() function:

Example:

The basic syntax for `predict()` in linear regression is-

```
predict(object,newdata)
```

Following is the description of the parameters used-


- * **object** - formula which is already created using `lm()` function.
- * **new data** - vector containing the value for prediction.

output:

predict the weight of a person & given $x(\text{height}) = 180$:

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Go to file/function Addins

```
~/   
predictor vector  
(176,154,148,166,172,124,190,135,155,161)
```

```
response vector  
(88,61,59,70,88,65,92,52,65,70)
```

```
fit the lm() function  
relation<-lm(y~x)
```

```
predict the weight of a person with height 180  
data.frame(x=180)  
fit<-predict(relation,a)  
print(result)  
1  
61
```

Visualize the regression Graphically:

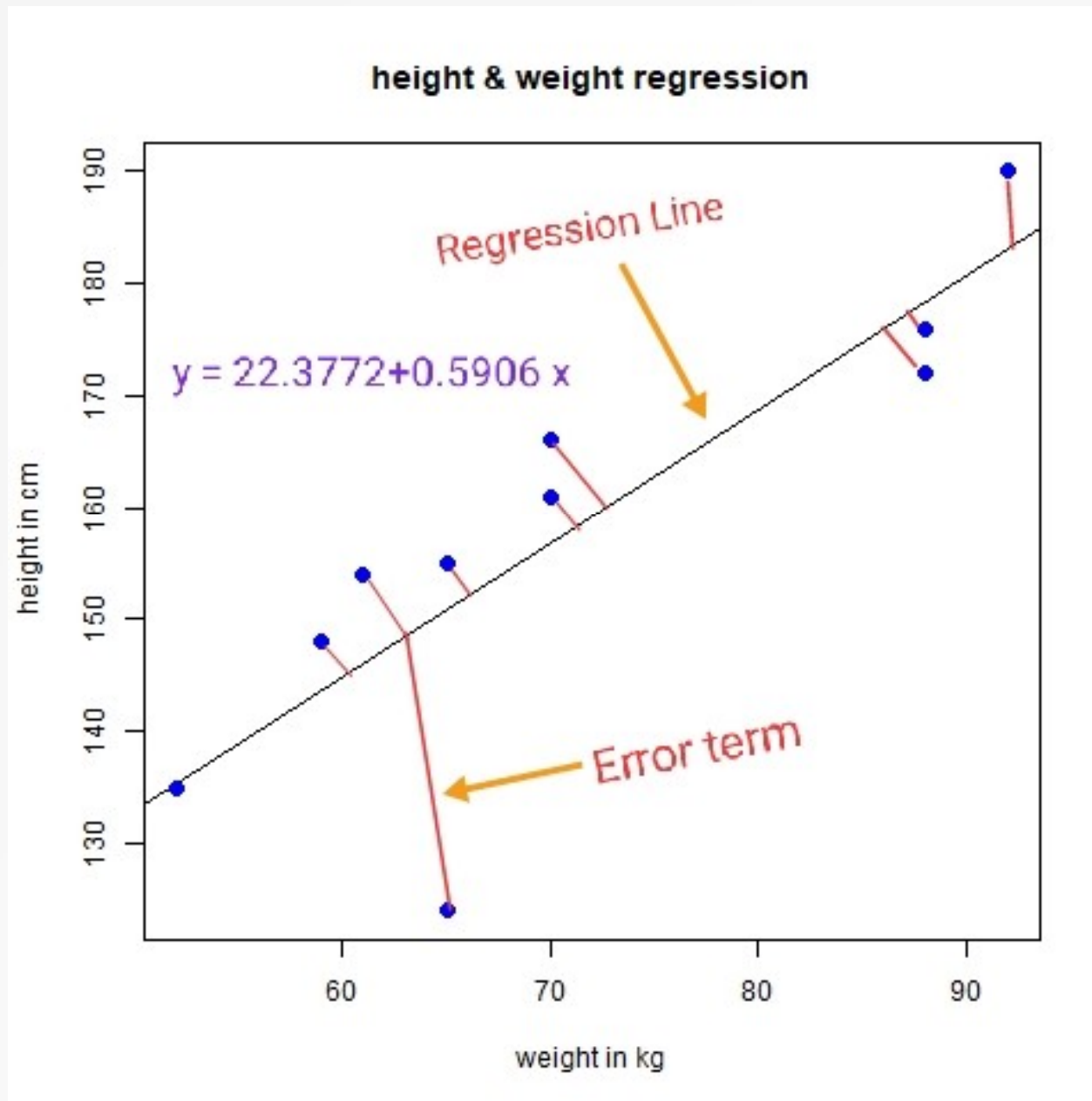
```
Studio
Edit Code View Plots Session Build Debug Profile Tools Help
Go to file/function Addins
Source
Console ~/ ↗
#create the predictor and response variable
x<-c(176,154,148,166,172,124,190,135,155,161)
y<-c(88,61,59,70,88,65,92,52,65,70)
relation<-lm(y~x)

#give the chart file a name
png(file="linearregression.png")

#plot the chart.
plot(y,x,col="blue",main="height & weight regression",abline(lm(x~y)),cex=1.3,pch=16,xl
="weight in kg",ylab="height in cm")

#save the file
dev.off()
[[ device
     1
```

graph:



result:

Regression equation of y on x;

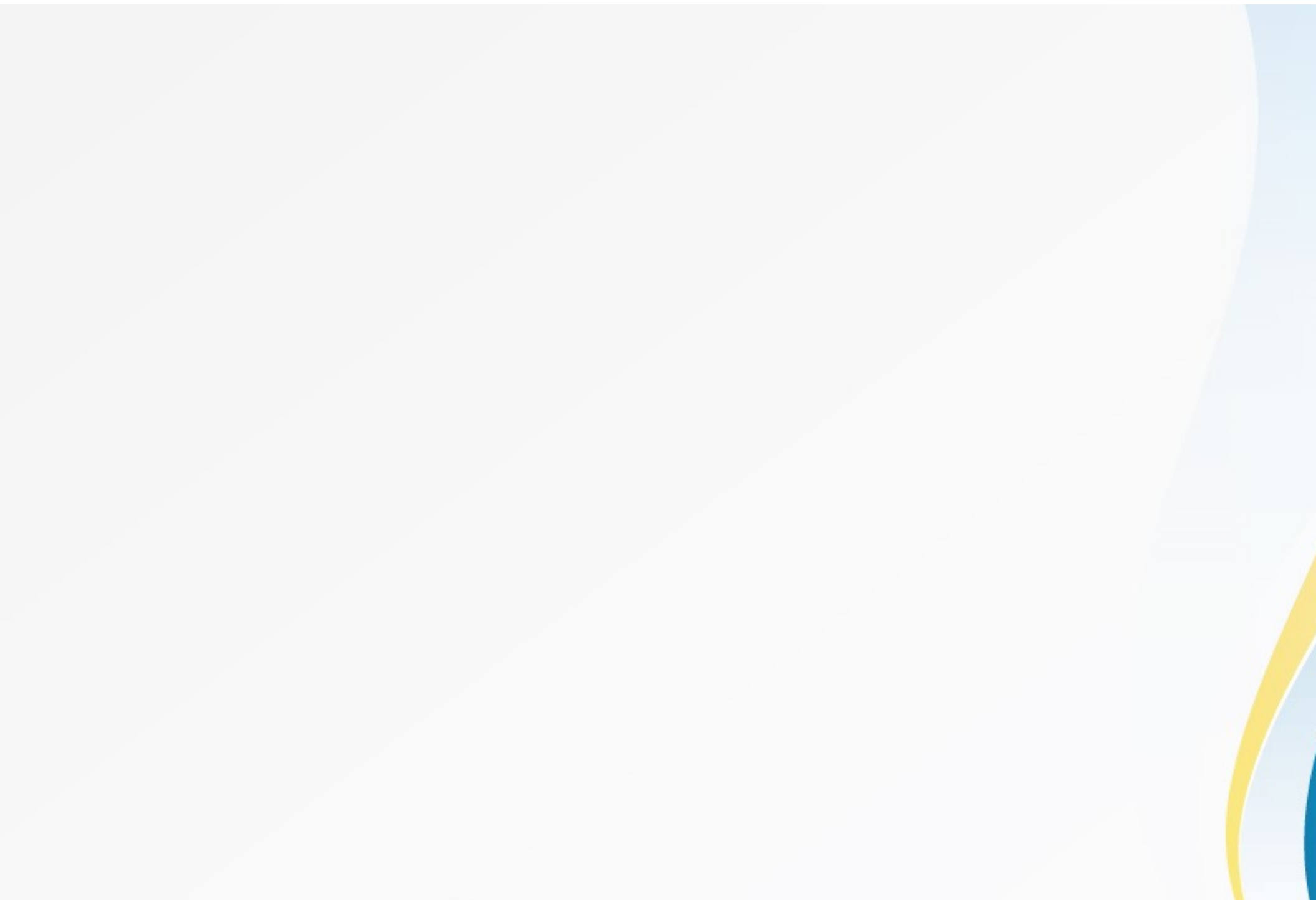
$$y = - 22.3772 + 0.5906 x$$

The predict value,

height of x =180 ,then weight of y = 83.934

THANK
YOU

A decorative graphic on the right side of the slide, consisting of overlapping curved shapes in light blue, yellow, and dark blue.



MULTIPLE REGRESSION USING R_LANGUAGE

REGRESSION

- Regression analysis is used to establish a relationship model between two variables.
- One of these variable is called independent variable whose value is gathered through experiments.
- The other variable is called dependent variable whose value is derived from the independent variable.
- Formula for regression

$$Y = \alpha + \beta X$$

MULTIPLE REGRESSION

Multiple regression is an extension of linear regression into relationship between more than two variables.

In simple linear relation we have one dependent and one independent variable, but in multiple regression we have more than one independent variable and one dependent variable.

FORMULA FOR MULTIPLE REGRESSION

The general mathematical equation for multiple equation is

$$Y = \alpha + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_n X_n$$

- Y is the dependent variable
- $\alpha, \beta_1, \beta_2, \dots, \beta_n$ are the parameter
- X_1, X_2, \dots, X_n are the independent variables

STEPS TO ESTABLISH A MULTIPLE REGRESSION

Step 1: Collect the data

Step 2: Capture the data in R

Step 3: Check for linearity

Step 4: Apply the multiple regression in R

Step 5: Make a prediction

the syntax for multiple regression:

$$\text{lm}(y \sim x_1 + x_2 + x_3 \dots, \text{data})$$

lm() Function:

This function creates the relationship model between the dependent and the Independent variable.

Input

Let's start with a simple example where our goal is to predict the stock_index_price (the dependent variable) of a fictitious economy based on two independent/input variables:

YEAR	2020	2020	2020	2020	2020	2020	2020	2020	2020
MONTH	10	9	8	7	6	5	4	3	2
INTEREST RATE	2.75	2.75	2.5	2.5	2.25	2.25	2.25	2	2
EMPLOYMENT RATE	5.3	5.3	5.3	5.3	5.4	5.6	5.5	5.5	5.5
STOCK INDEX PRICE	1464	1394	1357	1293	1256	1254	1234	1195	1159

Check for linearity

Before you apply linear regression models. Most notably, you'll need to check that a linear relationship exists between the dependent variable and the independent variables. A quick way to check for linearity is by using scatter plots.

In our example, we'll check that a linear relationship exists between:

the Stock_Index_Price (dependent variable) and the Interest_Rate (independent variable)

the Stock_Index_Price (dependent variable) and the Unemployment_Rate (independent variable)

yntax that can be used in R to plot the relationship between
e Stock_Index_Price and the Interest_Rate:

```
Year <- c(2020, 2020, 2020, 2020, 2020, 2020, 2020, 2020, 2020,  
2020)
```

```
Month <- c(10,9,8,7,6,5,4,3,2,1)
```

```
Interest_Rate <- c(2.75,2.75,2.5,2.5,2.25,2.25,2.25,2,2,2)
```

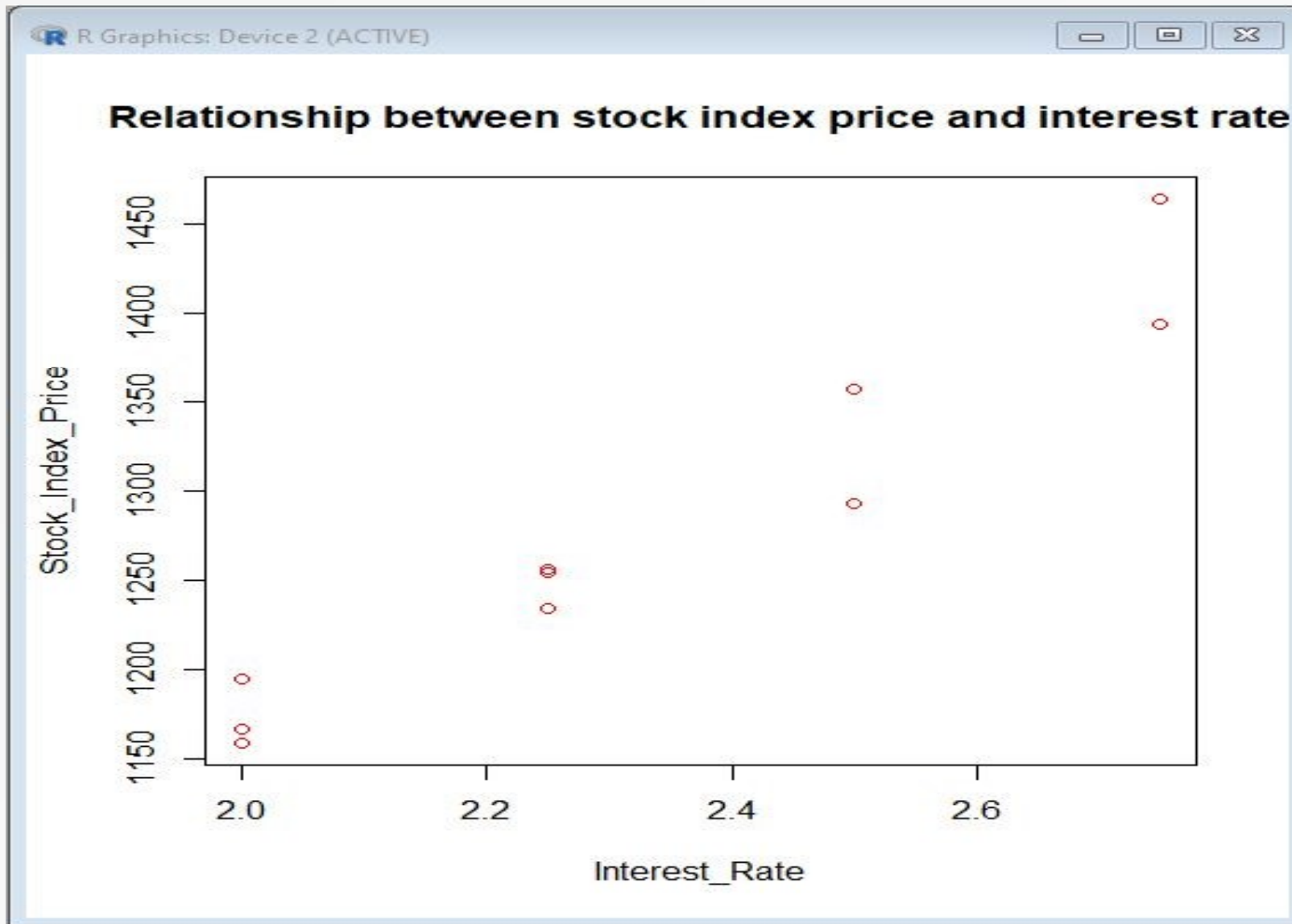
```
Unemployment_Rate <- c(5.3,5.3,5.3,5.3,5.4,5.6,5.5,5.5,5.5,5.6)
```

```
Stock_Index_Price <-
```

```
c(1464,1394,1357,1293,1256,1254,1234,1195,1159,1167)
```

```
plot(x=Interest_Rate, y=Stock_Index_Price, main='Relationship  
between stock index price and interest rate', col="red")
```


Scatter plot for relation between interest rate and stock index price



For the second case, you can use the syntax below in order to plot the relationship between the `Stock_Index_Price` and the `Unemployment_Rate`:

```
Year <- c(2020, 2020, 2020, 2020, 2020, 2020, 2020, 2020, 2020, 2020)
```

```
Month <- c(10,9,8,7,6,5,4,3,2,1)
```

```
Interest_Rate <- c(2.75,2.75,2.5,2.5,2.25,2.25,2.25,2,2,2)
```

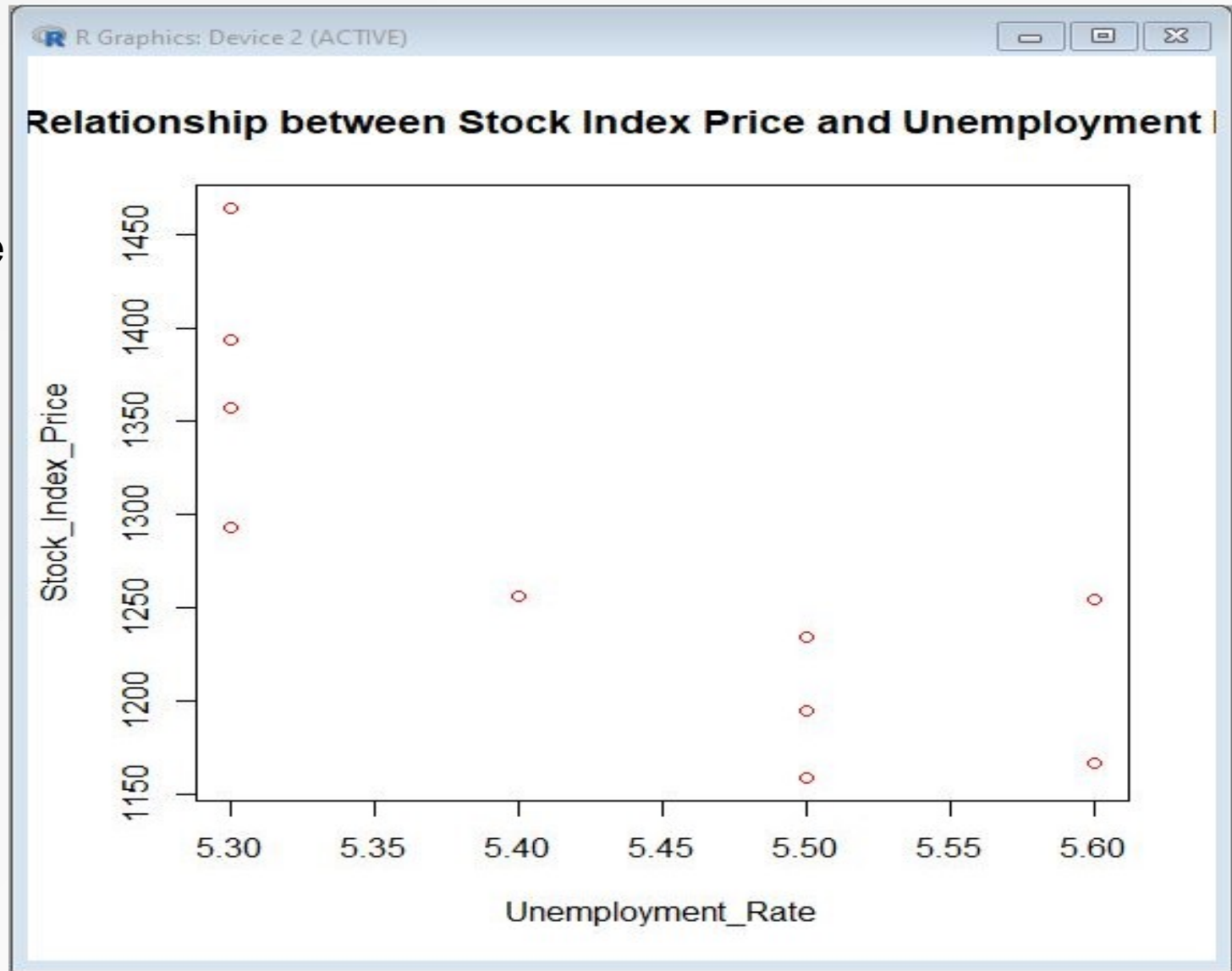
```
Unemployment_Rate <- c(5.3,5.3,5.3,5.3,5.4,5.6,5.5,5.5,5.5,5.6)
```

```
Stock_Index_Price <- c(1464,1394,1357,1293,1256,1254,1234,1195,1159,1167)
```

```
plot(x=Unemployment_Rate, y=Stock_Index_Price,main='Relationship between Stock Index Price and Unemployment Rate',col="red")
```

Scatter plot for relation between unemployment rate and stock index price

linear relationship
exists between the
Stock_Index_Price and the
Unemployment_Rate .
As the unemployment
rate goes up, the stock
index price goes down
(still have a linear
relationship, but with a
negative slope)



Apply the multiple regression in R

Using the syntax for our example:

```
Year <- c(2020, 2020, 2020, 2020, 2020, 2020, 2020, 2020, 2020, 2020)
Month <- c(10,9,8,7,6,5,4,3,2,1)
Interest_Rate <- c(2.75,2.75,2.5,2.5,2.25,2.25,2.25,2,2,2)
Unemployment_Rate <- c(5.3,5.3,5.3,5.3,5.4,5.6,5.5,5.5,5.5,5.6)
Stock_Index_Price <- c(1464,1394,1357,1293,1256,1254,1234,1195,1159,1111)
model <- lm(Stock_Index_Price ~ Interest_Rate + Unemployment_Rate)
summary(model)
```

output

When you run the code in R Language, you'll get the following output

```
Call:
lm(formula = Stock_Index_Price ~ Interest_Rate + Unemployment_Rate)

Residuals:
    Min       1Q   Median       3Q      Max
-42.483 -16.130  -0.442  17.183  44.216

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept)    458.707    894.398     0.513 0.623828
Interest_Rate  337.205     61.374     5.494 0.000912 ***
Unemployment_Rate  6.371    142.138     0.045 0.965502
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 29.41 on 7 degrees of freedom
Multiple R-squared:  0.9334,    Adjusted R-squared:  0.9143
F-statistic: 49.04 on 2 and 7 DF,  p-value: 7.631e-05
```

Summary

$$Y = \alpha + \beta_1 X_1 + \beta_2 X_2$$

Stock Index Price = (Intercept) + (Interest Rate coefficient)* X_1 + (Unemployment Rate coefficient)* X_2

Multiple Regression fit for Stock Index Price:

$$\text{Stock Index Price} = (458.707) + (337.205)*X_1 + (6.371)*X_2$$

make a prediction

For example, imagine that you want to predict the stock index price after you collected the following data:

Interest Rate = 1.5 (i.e., $X_1 = 1.5$)

Unemployment Rate = 5.8 (i.e., $X_2 = 5.8$)

And if you plug that data into the regression equation you'll get:

- Stock Index Price = $(458.707) + (337.205) * 1.5 + (6.371) * 5.8$**

The predicted value for the Stock Index Price is therefore 1001.4663